Dynamic Heterogeneous Robot Teams Engaged in Adversarial Tasks

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Abstract

As we progress towards a world where robots play an integral role, a critical problem that remains to be solved is that of dynamically formed heterogeneous robot teams where little information is known a-priori about the tasks, the robots, and the environments in which they will operate. We define this challenge as the Pickup Team Challenge. Successful solutions to forming pickup teams will enable researchers to experiment with larger numbers of robots; beyond what they can support and maintain. Additionally, enabling such teams will have a large impact on the ability of industry to efficiently and cost-effectively integrate new robot technology with existing legacy teams. In this paper, we define the challenge of pickup teams and relate its importance to multi-robot research. In our prior work, we have developed techniques for effective collaboration using market-based techniques and for synchronizing team activity through *plays*. We build on these prior approaches to move towards a complete system that is able to allocate roles amongst robots in a pickup team, and to execute synchronized team actions to accomplish a complex task.

Contents

1 Introduction

The vision that drives this work is that teams of robots will inevitably be an integral part of our future. Heterogeneous teams of robots will dynamically engage as partners in solving complex, potentially adversarial tasks by efficiently joining their complementary capabilities. There are significant, but not unachievable, challenges that must be overcome to realize this vision. These challenges include robust operation across multiple environments, building capabilities applicable across multiple robot types, and building teams of robots that improve over time.

Competitions, such as RoboCup, have been effective in focusing efforts to overcome some of these challenges [Noda et al., 1998, Veloso et al., 2000]. However, these competitions focus on part of the overall problem and do not address teams formed in an ad-hoc manner, complex environments beyond a well-defined soccer field, and the complexities of heterogeneous teams. Dynamic team formation addresses the problem of forming teams of robots in an impromptu, or pickup manner. That is, we assume that team members may have only minimal prior knowledge of each others behavior but are able to combine effectively. Thus, we address these challenges to realize our complete vision - teams of heterogeneous robots that form pickup teams dynamically to efficiently execute complex tasks. Specifically, we tackle two principal research agendas: efficient dynamic team formation, and robust, adaptable operation in multiple dynamic, potentially adversarial, environments.

There are several reasons why an increased understanding of pickup teams is needed. First, for large teams or for teams formed from expensive robots, it is impractical to develop these robots at the same site or at the same time. Furthermore, multi-robot research is currently hindered by the fact that it is often impractical to own large numbers of potentially expensive robots. Success in our investigation will facilitate further research by allowing separate researchers to easily pool their robots to create teams for further study. This means team members will have little detailed knowledge of each others algorithms in addition to other legacy issues. Our research contributes a principled methodology for the creation of pickup teams, increasing the opportunities for participation in the team. Second, robots may be needed for tasks, such as emergency ones, where there may be insufficient time to hand-engineer the coordination mechanisms before task execution. Our research will enable robot teams to be formed on very short-notice for such tasks. Third, as robots fail, get lost, or otherwise malfunction, it is often necessary to substitute or add new robots in place of the broken ones. A further understanding of pickup teams will enhance the integration of new robots into existing teams, and also enable teams of heterogeneous robots to perform efficiently under dynamic and uncertain conditions.

This paper focuses specifically on the problem of dynamically forming teams of heterogeneous robots. The robots have limited individual capabilities; they can sense information about their environment, and they can be assigned abstract tasks for execution. For example, they can autonomously reconnoiter a building and report on the presence or absence of specified objects of interest. Robots can solve these primitive tasks in several different ways depending on the robot capabilities and prevailing environmental conditions. These dynamically formed teams are able to adapt to unknown, dynamic and even adversarial environments, and efficiently execute complex tasks in a robust manner. Thus, dynamic and unknown obstacles, robot malfunctions, disruptions in communication, and depletions and additions to team resources are all handled gracefully and efficiently with team members adopting different roles best suited to efficiently executing the overall mission under the prevailing conditions. These research objectives are demonstrated and evaluated in a treasure hunt scenario.

2 Scenario

Our chosen scenario is a treasure hunt with two or more teams composed of heterogeneous robots competing to locate specific objects as they explore an unknown space. This scenario was developed by The Boeing Company based on discussions with the authors and our colleague Alex Rudnicky (Senior Systems Scientist, CMU). It represents a synthesis of many real world domains, such as space exploration, where multi-robot teams are likely to be employed in the future. Figures 1 and 2 show examples of the robots we use. The complexity of the scenario will increase over time. Initially, team composition will be fixed and the hunt will occur on a single floor within a building. Later, ad-hoc teams will be created from available resources and the hunt will move into outdoor areas. Teams will involve mixed groups of heterogeneous robots. Initially, the teams will compete only in the sense that they will race to finish first. In later years they will adopt adversarial strategies that directly engage the opposition.

This scenario offers a number of challenging aspects, including robust and efficient operation in unconstrained environments, and ad-hoc team formation. Efficient execution of this task will require a coordinated search of the space and the maintenance of an accurate shared knowledge about the space. For example, to create and maintain an accurate shared knowledge of what parts have been searched, and which objects of interest have already been located. In short, this scenario will provide a rich environment in which we can push back the boundaries of adaptive, autonomous robotics.

More specifically, the proposed scenario assumes that robots, which are de-

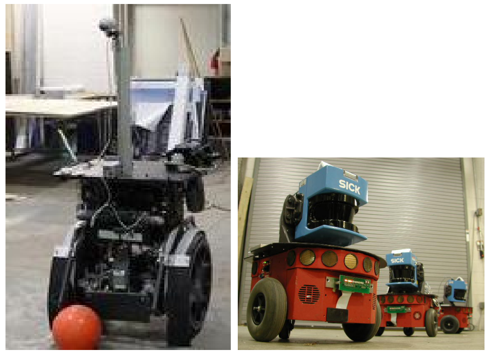

Figure 1: The left figure shows a segway robot, while the right figure shows the pioneer robots.

Figure 2: The left shows the Sony AIBO robots, the right the gator robots (which will be used for outdoor experiments).

signed and developed separately, should be brought together and enabled in a very short amount of time, e.g., 10 minutes or less, to work as a team and to execute tasks in a highly dynamic, uncertain and even adversarial environment. While some groups have focused on many research questions relevant to robot teams in the last several years (e.g. [Dias, 2004, Balch and (eds.), 2001, Madhavan et al., 2004, Parker et al., 2004]), no one has focused explicitly on the principles underlying such highly dynamic team building with minimal a-priori interaction between individual robot developers. Much of the existing research implicitly assumes that the robot team is built by a group of people who are working closely together over an extended period of time. While some previous research has addressed collaborations of software agents built by different groups [Pynadath and Tambe, 2003], no group has chosen to address the pickup challenge for multi-robot coordination. As such, significant research issues remain to realize our vision. We believe this research direction, forming dynamic teams, will greatly advance the science of multi-robot systems.

A final focal point of our research is building adaptive and robust teams. Thus we investigate different forms of component failures, disruptions in communication, dynamic obstacles, and changes in the sizes and capabilities of the teams to ensure efficient and robust performance of the teams under these conditions. We also test team performance in previously unknown and untested environments to ensure the ability of the teams to adapt to new environments and information. We believe that the principles developed within our scenarios will extrapolate readily to a broad variety of situations.

3 Technical Challenges

There are a number of challenges that must be surmounted in order to realize our vision of robust, dynamic ad-hoc robot teams. We outline the problem by casting it in terms of four key challenges:

1. Creating the individual team members
2. Forming an initial team
3. Coordinating the execution of the team task
4. Improving team performance over time

In the first challenge, different developers must be able to create their robots without requiring closely coupled development. The difficulty during this phase is how each developer should design the robot so that it will be able to work within any future teams assembled for a given task. In the second challenge, the robots are brought together for the first time in order to execute the given task and must be quickly organized into a team by allocating the most capable robots to the most appropriate roles. The difficulty here is that little time or human-power may be available. Indeed, our goal is that a solution should be automated and should take no more than 10 minutes. After these two issues are resolved, the robot team should be ready to begin execution. These first two challenges are fundamental to enabling a dynamic team.

Our remaining two challenges focus on improving team performance. In the third key challenge, the robots executing the task must coordinate their actions so as to obtain good team performance in a dynamic, uncertain, and potentially adversarial environment. Finally, the robot team improves its performance by learning during and after working together. The key issue here is how robots can create accurate models of each other and of the environment which enable them to reallocate roles and re-form the team as needed and also react to changes in the environment, and in team members, such as flat batteries, robot damage, robot replacement or augmentation. We propose key innovations for all four phases of creating robot teams. These contributions, when taken together, will enable the high quality dynamic teams.

4 Component Technologies

In this section we review our current approaches to teamwork – Skills, Tactics, and Plays (STP) for team coordination in adversarial environments, and TraderBots for efficient and robust role assignment in multi-robot tasks.

4.1 STP: Skills, Tactics, and Plays

In our prior work [Bruce et al., 2003, Bowling et al., 2004] we introduce the skills, tactics, and plays architecture (STP) for controlling autonomous robot teams in adversarial environments. Within this framework, teamwork, individual behavior, and low-level control are decomposed into three separate modules. Plays provide the mechanism for adaptive team coordination. Tactics provide the mechanism for individual robot control and are the action primitives for plays. Skills provide the mechanism for low-level, single robot control and are the action primitives for tactics. Tactics and skills are for single robot control and provide the high-level actions that a robot can perform for plays. Our focus in this paper will be on plays, and hence, we will not discuss tactics and skills in further detail, and instead refer the reader to previous publications [Bruce et al., 2003].

Plays are the central mechanism for coordinating team actions in an adversarial domain. Each play consists of the following components *(a)* a set of roles for each team member executing the play, *(b)* a sequence of actions for each role to perform, *(c)* an applicability evaluation function, *(d)* a termination evaluation function, *(e)* a weight to determine the likelihood of selecting the play.

Each play is a fixed team plan that describes a sequence of actions for each role in the team towards achieving the team goal(s). The actions in this case are tactics that each robot can perform. Each of the roles is assigned to a unique team member during execution. The role assignment is based on the believed state of the world and is dynamic (e.g. role A may start with player 1, but may switch to player 3 as execution progresses). Note that the role assignment mechanism is independent of the play framework.

The concept of plays was created for domains where tight synchronization of actions between team members is required. Therefore, the sequence of tactics to be executed by each role is executed in lock step with each other role in the play. Hence, the play forms a fixed team plan whereby the sequence of activities is synchronized between team members.

As not all plans are appropriate under all circumstances, each play has a boolean evaluation function that determines the applicability of the play. This function is defined on the team's belief state, and determines if the play can be executed or not. Thus, it is possible to define special purpose plays that are applicable only under specific conditions as well as general-purpose plays that can be executed under much broader conditions. Once executed, there are two conditions under which the play can terminate. The first is that the team finishes executing the team plan. Each play includes an evaluation function that determines whether the play should be terminated. As with applicability, this evaluation function operates over the team's belief state. Hence, the second means of ending a play is if the termination evaluation function determines that the play should end, either because it has failed or is successful.

Team strategy consists of a set of plays, called a playbook, of which the team can execute only one play at any instant of time. A play can only be selected for execution if it is applicable. From the set of applicable plays, one is selected at random with a likelihood that is tied to the play's weight. The plays are selected with a likelihood determined by a Gibbs distribution from the weights over the set of applicable plays. This means the team strategy is in effect stochastic. This is desirable in adversarial domains to prevent the team strategy being predictable, and therefore exploitable by the opponent.

The final mechanism to complete play-based coordination in adversarial environments, is to adapt the weights for each play to improve team performance. That is, a mechanism to adapt the likelihood of selecting a play based on the observed performance of the team. [Bowling et al., 2004] modifies a play's weight using a sleeping experts-based approach. Depending upon the success or failure of the play execution, the weight is increased or decreased such that it is guaranteed to minimize the regret of the team in the limit. The approach modifies the weight values based on the way a play terminates its execution. In particular, if a play completes, or succeeds in achieving its goals (as determined by the termination function), the weight is modified to increase the future selection likelihood of that play. Conversely, if the team plan terminates for any other reason, the weight is modified to decrease the future selection likelihood.

4.2 TraderBots

TraderBots, developed by Dias and Stentz ([Dias and Stentz, 2000, Dias, 2004, Dias et al., 2004]) is a coordination mechanism designed to inherit the efficacy and flexibility of a market economy, and to exploit these benefits to enable robust and efficient multirobot coordination in dynamic environments. A brief introduction to this approach is presented here.

Consider a team of robots assembled to perform a set of tasks in a dynamic environment. Consider further, that the team of robots is modeled as an economy, and each robot in the team is modeled as a self-interested trader in this economy. Thus, the goal of the team is to complete the tasks successfully, maximizing overall profits (i.e. the difference between revenue and cost), while each robot aims to maximize its individual profit. Thus, robots conduct auctions to determine task allocations within the team, and the different tasks and information are the commodities traded in the economy. A system such as this inherits many desirable characteristics from the market methodology. The competitive element of the robots bidding for different tasks enables the system to decipher the competing local information of each robot with no requirement for a central agent evaluating information and planning for the entire system, while the common currency provides grounding for the competing local costs in relation to the global priorities of the tasks assigned to the team.

- **Revenues, Costs, and Price**

  Appropriate functions are needed to map possible task outcomes onto revenue values and to map possible schemes for performing the task onto cost values. As a team, the goal is to execute some plan such that the overall profit, is maximized. Furthermore, these functions must provide a means for distributing the revenue and assessing costs to individual robots. Thus, robots receive revenue and incur costs for accomplishing a specific team-task, but the team's revenue function is not the only source of income. A robot can also receive revenue from another robot in exchange for goods or services. The price dictates the payment amount for the good or service.

- **Cooperation and Competition**

  In general within TraderBots two robots are cooperative if they have complementary roles; that is, if both robots can make more profit by working together than by working individually. Conversely, two robots are competitive if they have the same role; that is, if the amount of profit that one can make is negatively affected by the presence of the other robot. The flexibility of the market-model allows the robots to cooperate and compete as necessary to accomplish different tasks.

- **Self Organization**

  Conspicuously absent from the TraderBots approach is a rigid, top-down hierarchy. Instead, the robots organize themselves in a way that is mutually beneficial. Since the aggregate profit amassed by the individuals is directly tied to the success of the task, this self-organization yields the best results. However, TraderBots also allows the flexibility of dynamically forming subgroups with leaders to enhance optimization ([Dias and Stentz, 2002]).

- **Learning and Adaptation**

  Within the TraderBots framework, the team can learn new behaviors and strategies as it executes its tasks. This learning applies to both individual behaviors and negotiations as well as to those of the entire team. Another strength of the TraderBots approach is its ability to deal successfully with dynamic conditions. Since it does not rely on a hierarchical structure for coordination and task assignment, the approach is highly robust to changes in the environment, including malfunctioning robots. Disabling any single robot does not jeopardize the system's performance.

Thus, TraderBots enables robots to robustly accomplish efficient task allocation. The approach also enables team execution of complex tasks in dynamic environments in an opportunistic and adaptive manner.

5 Joint Teaming Strategy

From our prior work, we have established that STP is a robust technique for synchronizing activities across a team operating in an adversarial environment. Similarly, we have shown that TraderBots is a robust technique for assigning roles in a complex task domain. The treasure hunt scenario described in section 2 requires both of these capabilities as the environment is complex, dynamic and adversarial. Task assignment is non-trivial and very challenging given the pickup team component of the problem. Finally, the problem domain requires more than task assignment to be satisfactorily solved. In many situations, the whole team or subteams will need to tightly synchronize their activities in order to effectively solve the problem.

In particular, our goals are: *(a)* Merging STP and TraderBots such that plays control team coordination during execution, while TraderBots provides robust mechanisms for role assignment, *(b)* extending plays to enable more complex and flexible synchronization mechanisms, *(c)* extending TraderBots to enable unfamiliar teammates to negotiate on capabilities in order to define both role assignments, and valid plays, *(d)* extending both STP and TraderBots to incorporate learning mechanisms to improve team performance through joint experience, and *(e)* improving robustness in all aspects of the system. With these goals in mind, we address the four key challenges to realizing pickup teams as follows.

- **How can a robot be a member of the team?**

  Designing robots that can obtain membership in an effective pickup team requires describing a flexible team task specification language that will define tasks in terms of roles and capabilities. Moreover, this language is designed to be flexible enough to accommodate a wide range of heterogeneous robots in those roles. Each role is defined in terms of the specific capabilities and includes an evaluation function, which measures how well the robot matches the requirements. Given this specification, anyone will be able to develop a robot for some set of roles. The team task specification language provides a way for a robot to communicate its potential roles and capabilities to other robots, so that plans can be generated and task assignments made.

- **How is an initial team formed?**

  The robots self-organize into a team using the TraderBots market architecture that selects the plan or plans that maximizes their individual profits. The candidate plans include optimization algorithms to assign roles based on robot characteristics, task requirements, and environmental conditions which need to operate over a rich capability representation. Previous approaches have reduced capabilities to single numeric values, while in teams of robots we have to define richer structures to include perception, planning, and action capabilities.

- **How does a group of robots execute synchronized action as a team?**

  We build upon our capability representations to contribute mechanisms for executing coordinated actions from a set of fixed-team-plans agreed upon during the pre-task team formation. Coordinated execution is via fixed-team-plans where the selection, execution direction, and monitoring of the plan are directed by the team leaders whose plans were adopted (using the TraderBots approach) during the team formation process.

- **How can the teams improve with experience?**

  We contribute learning algorithms for improving dynamic team performance during and after each task execution. Learning within the dynamic team formation context will take two forms: through better team plan selection during execution, and by modeling the environment and observed capabilities of teammates. The latter will improve future team formation, and role assignment, by providing better estimates of robot's true capabilities and the costs of performing a task as a function of the its membership in the team.

5.1 Illustrative example

To illustrate our approach, we use the following example drawn from the problem domain. The example is broken into two components: team formation, and execution. Team formation, which occurs prior to initial execution and can occur flexibly throughout execution, is a process of exchanging capabilities and using TraderBots to determine sub-team structure. In the scenario described here, this means exchanging perception abilities of each robot. For example, the pioneer robots are equipped with laser range finders and can therefore effectively map and localize. In contrast, segway robots are equipped with cameras and are able to identify the 'treasure' visually, and track pioneer robots. In this case, it is clear that both types of robot need to combine to form effective sub-teams. In the process of forming sub-teams, robots must also exchange knowledge of different plays. The key to this approach is that while knowledge of available tactics are necessary, detailed knowledge of tactic implementations is not required. Play selection and execution operate as before. During execution each robot monitors the progress of the play. If the play must terminate either due to success or failure, the selection probability is updated accordingly.

6 Summary and Future work

In this paper, we presented the concept of pickup teams, where teams are formed dynamically from heterogeneous robots with no a-priori experience of one another. We have presented an appropriate domain for exploring the research issues related to pickup teams – multi-robot treasure hunts. Based on our prior work with synchronized activities using STP with plays and tactics combined with robust multi-robot role assignment using the TraderBots market-based architecture, we have proposed a new technique to address the problem of pickup teams.

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